



Efficient Adaptive Beam Steering using Interference Normalization Least Mean Square Algorithm based Smart Antenna in Wireless Sensor Networks

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Abstract: Wireless Sensor Networks are increasingly being employed for monitoring and sensing in harsh environments such as factories and offshore platforms. This technology has the potential to offer measurements over larger and difficult to access areas, giving more up-to date and precise information to inform control and operational systems. Wireless sensor networks are ideal for the development of the envisioned world of ubiquitous and pervasive computing. Energy and computational efficiency constraints are the main key issues when dealing with this type of network. One of the challenges facing the development and adoption of wireless sensor networks is achieving wireless communications which is energy efficient yet robust and resilient. Being low cost and battery powered, wireless sensors have limited resources, which must be used optimally. Large Beam efficient smart antennas can give significant improvement in communications performance, and recent developments in parasitic array techniques have led to low power, low cost smart antennas. In this research, an interference-normalized least mean square (INLMS) algorithm for wireless sensor network is proposed. The INLMS algorithm extends the gradient-adaptive learning rate approach to the case where the signals are non-stationary, we also compare the performance of proposed smart antenna scheme with existing LMS and NLMS algorithms. Comparison is done through the performance matrices like, Beam-width, throughput, End-to-End Delay, Network Lifetime etc. and it is found that wireless sensor network with proposed smart antenna scheme out perform the existing approaches.

Keywords: Wireless sensor network, Smart Antenna, Interference Normalization Least Mean Square [INLMS]Algorithm , Normalized least mean square (NLMS) algorithm, Least mean square (LMS).

I. INTRODUCTION

Wireless sensor networks (WSNs) are a class of distributed computing and communication systems that are an integral part of the physical space they inhabit [1]. This type of network is characterized by nodes with a low profile, having limited computational power and sparse energy resources, which have the ability to collaborate with each other, and to sense, reason, and react to the world that surrounds them. Recent advances in this field have enabled the development of wireless sensor networks, the functionality of which rely on the collaborative effort of a large number of tiny, low-cost, low-power, multi-functional sensor nodes that are able to communicate un-tethered over short distances [2,3]. Moreover, engineering or predetermining the positions of the nodes is not necessary. This allows random deployment in hostile environments or disaster-relief operations, a unique feature that accounts for rendering these network types an integral part of modern life. Smart environments represent the next evolutionary

development step in the automation of building, utility, industrial, home, shipboard, and transportation systems [4].

This bridge to the physical world has enabled a growing bouquet of added-value services, ranging from health to military and security, such as target tracking, environmental control, habitat monitoring, source detection and localization, vehicular and traffic monitoring, health monitoring, building and industrial monitoring, etc. [5].

On the other hand, wireless sensor networks display certain undesirable or hard-to-deal-with features. These include power limitations, frequently changed topology, broadcast communication, susceptibility to failure, and low memory, while their architecture calls for protocols and algorithms with self-organizing capabilities [2]. In most cases, a wireless sensor network will be composed of a large number of densely deployed sensor nodes. Neighboring nodes might

be very close to one another, resulting in high interference and power consumption levels. Furthermore, one of the most important constraints of sensor nodes stems from their limited – generally, irreplaceable – power sources. Therefore, while traditional networks aim at achieving high quality of service (QoS) provisions, wireless-sensor-network protocols must focus primarily on power conservation. Tradeoff mechanisms seem necessary to increase reliability at the cost of lower throughput or higher latency. An essential design issue is related to the investigation of system parameters, such as network size and node density, with regards to system metrics including spatial coverage, throughput, latency, network lifetime, energy efficiency, and reliability, and how these affect the tradeoffs previously mentioned.

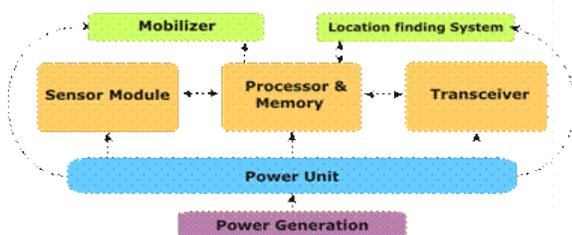


Fig 1: Hardware architecture of a sensor node

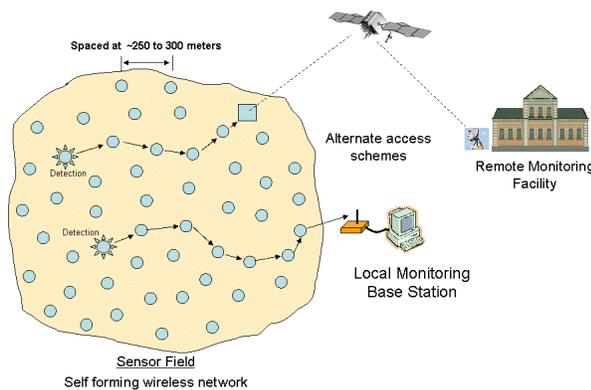


Fig 2: Overview of WSN

These issues have been engaged in the literature, with most approaches having focused on routing optimization and protocol design. Many researchers have developed schemes that fulfill the requirements described above, proposing protocols and algorithms for wireless sensor networks. Quality of service can be measured in terms of energy efficiency, or the optimum number of sensors sending information at any given time [6, 7]. In the latter case, quality-of-service control mechanisms, built on the Gur Game Paradigm, have been put forward to adjust quality-of-

service resolution, thus extending network lifetime and managing energy depletion. Later, J. Frolik [8] extended the Gur game approach, and, additionally, illustrated a second method providing quality-of-service feed back through packet acknowledgments. Apart from the introduction of new MAC-layer protocols (Quality-of-service-specific Information REtrieval (QUIRE)) [9], Z-MAC [10], i-GAME), and network-layer protocols, e.g., MMSPEED [11], cross-layer design is a novel approach that has lately come under close scrutiny.

Minimizing node interference is undoubtedly one of the main challenges in wireless sensor networks. High interference increases the packet-collision probability, which, in turn, affects efficiency and energy consumption. Early approaches focused on reducing the node degree [12, 13]. Topology control mechanisms inspired by graph theory have been developed to conserve energy in wireless sensor networks without being able to explicitly guarantee low interference. Some examples include the work of Burkhart et al., using a minimum spanning tree (MST) [14]; the highway model, proposed by Rickenbach et al. [15]; and the “Minimizing Interference in Sensor Network (MI-S)” algorithm introduced by A. K. Sharma et al. In addition, Jang [16] drew inspiration from graph theory to propose geometric algorithms, reducing interference based on the conversion of network problems to geometry problems. Last, J. Tang et al. [17] studied multi-channel assignments to achieve interference-aware topology control in wireless mesh networks.

II SMART ANTENNA

On the other hand, smart antennas have been extensively used in the literature of more conventional communications systems, and their usage is likely to expand more, due to their proven beneficial impact in wireless communications performance [18]. Smart antennas have been suggested in order to satisfy the demand for spontaneously high data rates to certain users, while maintaining a high level of quality of service for conventional users [19]. They have been also used in order to mitigate interference and delay spread, increase system capacity and spectral efficiency, combat multipath fading, address the near-far effect, and increase cell coverage [20]. Furthermore, they have been suggested for radiation-pattern diversity, space-division multiple access, direction-of-arrival estimation and localization, etc.

Throughout the world, there is significant research and development on smart antennas for wireless systems. Smart antenna systems attract a lot attentions now and believably more in the future, as it can increase the capacity of mobile communication systems dramatically [26]. This is because smart antennas have tremendous potential to enhance the performance of future generation wireless systems as evidenced by the antennas’ recent deployment in many

systems. There are two basic types of smart antennas. The first type is the phased array or multi beam antenna, which consists of either a number of fixed beams with one beam turned on towards the desired signal or a single beam (formed by phase adjustment only) that is steered toward the desired signal. The other type is the adaptive antenna array is an array of multiple antenna elements, with the received signals weighted and combined to maximize the desired signal to interference plus noise power ratio [23].

A smart antenna system at the base station of a cellular mobile system is depicted in Figure 3[3]. It consists of a uniform linear antenna array for which the current amplitudes are adjusted by a set of complex weights using an adaptive beam forming algorithm. The adaptive beam forming algorithm optimizes the array output beam pattern such that maximum radiated power is produced in the directions of desired mobile users and deep nulls are generated in the directions of undesired signals representing co-channel interference from mobile users in adjacent cells. Prior to adaptive beamforming, the directions of users and interferes must be obtained using a direction-of- arrival (DOA) estimation algorithm.

The goal of direction-of-arrival (DOA) estimation is to use the data received on the downlink at the base-station sensor array to estimate the directions of the signals from the desired mobile users as well as the directions of interference signals [27]. The results of DOA estimation are then used by to adjust the weights of the adaptive beam former so that the radiated power is maximized towards the desired users, and radiation nulls are placed in the directions of interference signals. Hence, a successful design of an adaptive array depends highly on the choice of the DOA estimation algorithm which should be highly accurate and robust.

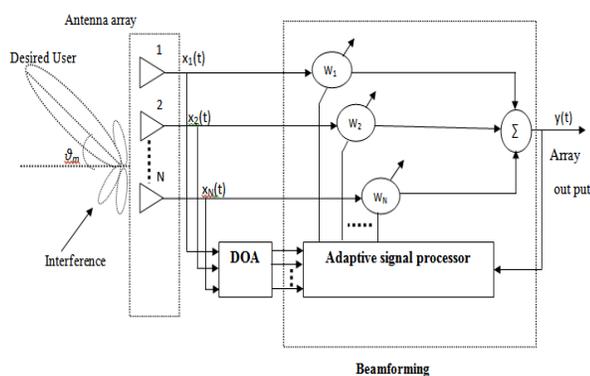


Fig 3 : Block diagram of smart antenna

Adaptive smart antennas are the array antennas whose radiation pattern is shaped according to some adaptive algorithms [1]. Smart essentially means computer control of the antenna performance. The smart antenna radiation pattern directs the beam towards the users of interest only & nulls toward interference to improve the capacity of cellular

system. The adaptive beam forming algorithms takes the fixed beam forming process one step further & allows for the calculation of continuously updated array weights.

According to signal space information smart antenna can form directional beam in space with the adaptive beam forming algorithm, achieving that the main beam aims at the direction of the expected signal while the side lobe and nulls aims at the interference. Now many adaptive algorithms have been proposed on smart antenna. The INLMS, NLMS algorithm and LMS algorithm are most commonly used as a adaptive beam forming algorithm .

In this research, an interference-normalized least mean square (INLMS) algorithm for wireless sensor network is proposed. The INLMS algorithm extends the gradient-adaptive learning rate approach to the case where the signals are non-stationary, we also compare the performance of proposed smart antenna scheme with existing LMS and NLMS algorithms. Comparison is done through the performance matrices like, Beam-width, throughput, End-to-End Delay, Network Lifetime etc. and it is found that wireless sensor network with proposed smart antenna scheme outper form the existing approaches.

III INLMS Algorithm

An **interference-normalized least mean square (INLMS) algorithm** for robust adaptive filtering is proposed. The INLMS algorithm extends the gradient-adaptive learning rate approach to the case where the signals are nonstationary. In particular, we show that the INLMS algorithm can work even for highly nonstationary interference signals, where previous gradient-adaptive learning rate algorithms fail.

The choice of learning rate is one of the most important aspects of least mean square adaptive filtering algorithms as it controls the tradeoff between convergence speed and divergence in presence of interference. In this letter, we introduce a new interference-normalized least mean square (INLMS) algorithm. In the same way as the NLMS algorithm introduces normalization against the filter input $x(n)$, our proposed INLMS algorithm extends the normalization to the interference signal $u(n)$. The approach is based on the gradient-adaptive learning rate class of algorithms [1]–[4], but improves upon these algorithms by being robust to nonstationary signals. We consider the adaptive filter illustrated in Fig. 1, where the input signal $x(n)$ is convolved by an unknown $h(n)$ filter to produce $y(n)$. which has an additive interference signal $u(n)$, before being observed as $d(n)$. The adaptive filter attempts to estimate the impulse response $h(n)$ to be as close as possible to the real impulser esponse $h(n)$ based only on the observable signals $x(n)$ and $d(n)$.The estimated convolved signal $y(n)$ is subtracted from $d(n)$, giving an output signal $e(n)$ containing both the interference $u(n)$ and a residual signal $r(n)=y(n)-$

$y(n)$. In many scenarios, such as echo cancellation, the interference $u(n)$ is actually the signal of interest in the system. The standard normalized least mean squares (NLMS) algorithm is given by

$$e(n) = d(n) - \hat{\mathbf{h}}^H(n-1)\mathbf{x}(n) \quad (1)$$

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{\mu(n)}{\|\mathbf{x}(n)\|^2} e^*(n)\mathbf{x}(n) \quad (2)$$

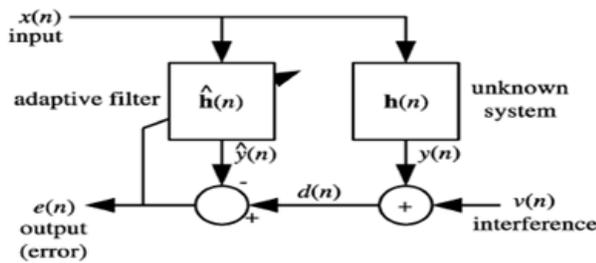


Fig 4 : Block diagram of Echo cancellation system

where $\mathbf{x}(n) = [x(n), x(n-1), \dots, x(n-L+1)]^T$ and $\mu(n)$ is the learning rate. Here, we propose to extend this algorithm, by adaptively updating $\mu(n)$. By adopting our approach, we develop an algorithm which we call the INLMS algorithm and which works even for highly nonstationary interference signals, where previous gradient-adaptive learning rate algorithms fail.

IV NLMS Algorithm

The normalized least mean square (NLMS) algorithm

NLMS algorithm has been implemented in Matlab. As the step size parameter is chosen based on the current input values, the NLMS algorithm shows far greater stability with unknown signals [6]. This combined with good convergence speed and relative computational simplicity make the NLMS algorithm ideal for the real time adaptive echo cancellation system. As the NLMS is an extension of the standard LMS algorithm, the NLMS algorithms practical implementation is very similar to that of the LMS algorithm. Each iteration of the NLMS algorithm requires these steps in the following order [7].

1. The output of the adaptive filter is calculated

$$y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) = \mathbf{w}^T(n)\mathbf{x}(n) \quad (3)$$

2. An error signal is calculated as the difference between the desired signal and the filter output

$$E(n) = d(n) - y(n) \quad (4)$$

3. The step size value for the input vector is calculated

$$\mu(n) = \frac{1}{\mathbf{x}^T(n)\mathbf{x}(n)} \quad (5)$$

4. The filter tap weights are updated in preparation for the next iteration.

$$\mathbf{W}(n+1) = \mathbf{W}(n) + \mu(n)e(n)\mathbf{x}(n) \quad (6)$$

Each iteration of the NLMS algorithm requires $3N+1$ multiplications, this is only N more than the standard LMS algorithm. This is an acceptable increase considering the gains in stability and echo attenuation achieve.

V LMS Algorithm

The **Least Mean Square (LMS) algorithm**, is an adaptive algorithm. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Beam forming is directly determined by the two factors. This algorithm can be applied to beam forming with the software Matlab. The result obtain can achieve faster convergence and lower steady state error. The algorithms can be simulated in MATLAB 7.10 version.

Consider a L length LMS based adaptive filter in which ‘ \mathbf{W} ’ is the weight vector updated in accordance with the statistical nature of the input signal $x(n)$ arriving from the antenna array. An adaptive processor will minimize the error $e(n)$ between a desired signal $d(n)$ and the array output $y(n)$. The knowledge of the received signal eliminates the need for beam forming, but the reference can also be a vector which is somewhat correlated with the received signal. As shown in Fig.2.

The output response of the uniform linear array is given by

$$y(n) = \hat{\mathbf{h}}^H(n)\mathbf{x}(n) \quad (7)$$

We consider the adaptive filter where the input signal $x(n)$ is convolved by an unknown $h(n)$ filter (to produce $y(n)$) which has an additive interference signal $v(n)$ before being observed as $d(n)$.

The value of error signal estimation is

$$e(n) = d(n) - y(n) \quad (8)$$

The estimated convolved signal

$$r(n) = y(n) - \hat{y}(n) \quad (9)$$

we arrive at the recursion for the LMS adaptive algorithm for updating the step as

$$h(n) = h(n-1) + 2\mu e(n)\mathbf{x}(n) \quad (10)$$

where μ is constant step and the filter taps can be adaptively updated by using above recursive relation.

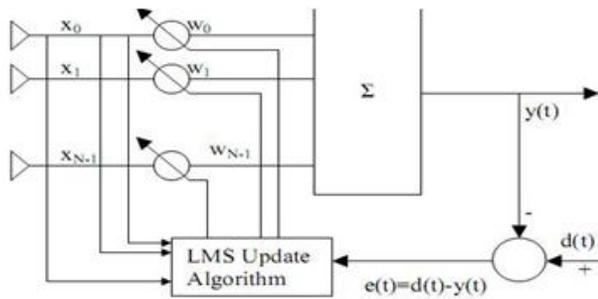


Figure 5: LMS adaptive Beamforming Network

NLMS converge faster than LMS because the step size is optimized at each iteration. The computational complexity of the more in NLMS than LMS. But INLMS is better than NLMS & LMS algorithms.

VI SYSTEM MODEL

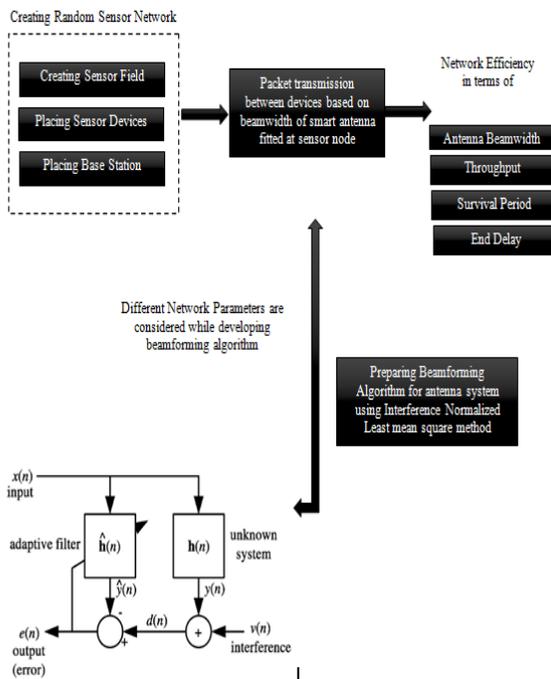


Fig 6: System model of efficient adaptive beam steering Using INLMS based Smart antenna in WSN

VII SIMULATION RESULTS

Initially creating a 10000 square meter field area for modelling of network, this value can be change as per requirements. (x=100 m and y=100 m)

Placing Network devices on the graph, these are number of sensors and base station which gather data from sensors. Sensor are selected manually from user end and base station

is placed at the center of field initially. All the sensor devices are placed randomly in the field without any placing criteria. After that the antenna and network initial values which we take, this can be change from user end as per requirement.

SIMULATION PARAMETERS

- **End-to-end delay**

End-to-end delay refers to the time taken for a packet to be transmitted across a network from source to destination.

- **Throughput**

Throughput or network throughput is the average rate of successful message delivery over a communication channel. This data may be delivered over a physical or logical link, or pass through a certain network node. The throughput is usually measured in bits per second (bit/s or bps), and sometimes in data packets per second or data packets per time slot.

- **Efficiency**

The ratio of the number of messages successfully delivered from source to destination, to the total network load generated throughout the simulation.

- **Percentage of active nodes, a (%)**

The average number of nodes allowed to transmit within the same time slot without being blocked due to interference caused by ongoing network traffic. A small percentage of active nodes corresponds to more collisions, which reduces network efficiency.

S.No	Parameters	Parameters Assumption
1	No. of Sensors	100
2	Create field area	10000 sq meter
3	Snap number	100
4	Sample frequency	1.8e+010 Hz
5	No of Arrays	16
6	Working frequency	3e+0.09 Hz
7	Working Wavelength	0.1 meter
8	Array distance	0.05 meter
9	SNR	0 db
10	JNR ₁	30
11	JNR ₂	30
12	JNR ₃	30
13	Angle 0	15 degree
14	Angle 1	25 degree
15	Angle 2	00 degree
16	Angle 3	-15 degree

Table 1

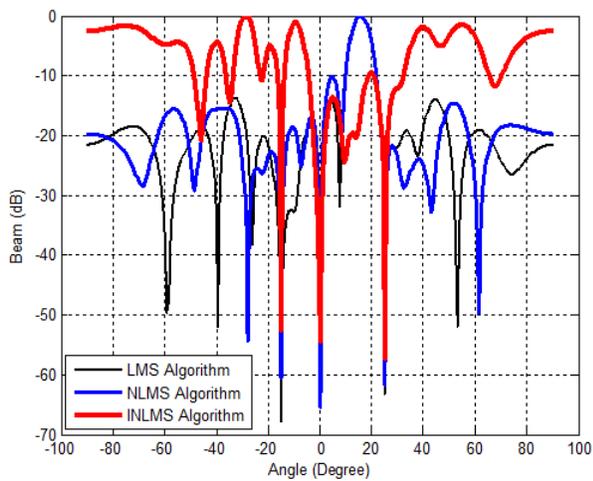


Fig 7: Beam pattern using INLMS (Amplitude response antenna pattern)

Figure shows that the Comparison of Beam pattern (beam width with respect to angle) for LMS, NLMS and Proposed INLMS algorithm. In that fig INLMS algorithm beam pattern is best in comparison of NLMS & LMS algorithms.

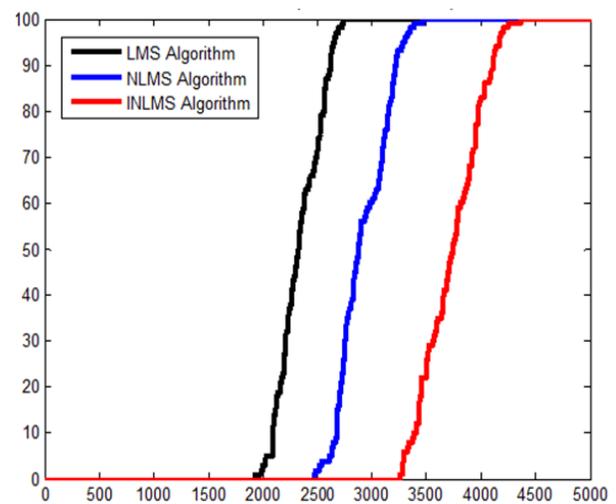


Fig 9: Active nodes with respect to transmission period

Figure shows that Active Nodes in network with respect to transmission period in All the three cases here packets delivery is depends upon the beam pattern of antenna.

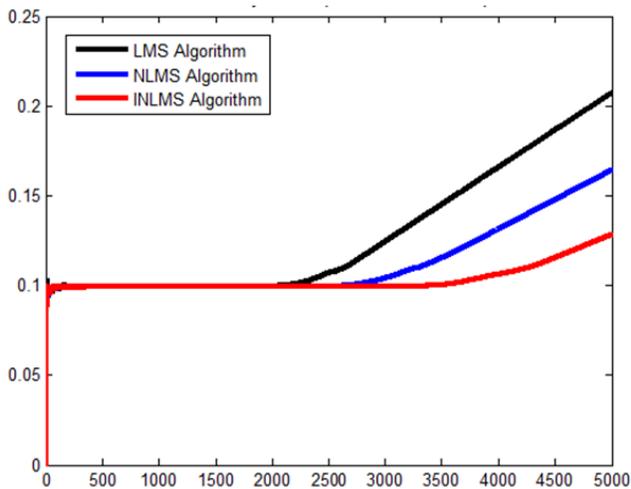


Fig 8: End to end delay with respect to transmission period.

Figure shows End to End delay in packet delivery in network with respect to transmission period in all the three cases, here packets delivery is depends upon the beam pattern of antenna.

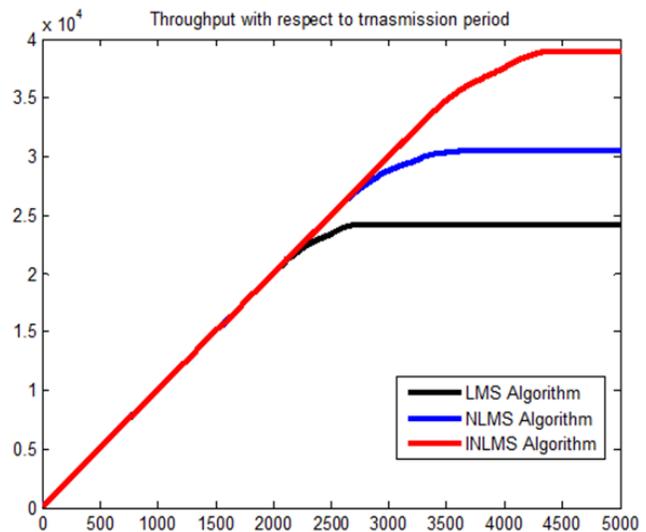


Figure 10: Throughput with respect to transmission period

Figure shows that Throughput in network with respect to transmission period in all the three cases, here packets delivery is depends upon the beam pattern of antenna.

VIII CONCLUSION & FUTURE WORK

A wireless sensor network (WSN) consists of small autonomous low-cost low-power devices that carry out monitoring tasks. Initially developed for military use, WSNs can now a days be found in many civil applications, such as



environmental monitoring, biomedical research, seismic monitoring, and precision agriculture. Several methods, which are based on cooperative signal enhancement, were developed to overcome the difficulty of long distance transmissions and energy inefficiency in WSNs where sensor nodes are deployed over a wide area. These methods include Smart Antennas, Cooperative MIMO, and a relatively new technique Distributed Beamforming.

The multi disciplinary field of smart antennas has become significantly important over the past two decades. In this paper constrained interference normalized least mean square (INLMS) algorithm for narrowband adaptive beamforming has been derived. This algorithm is capable of efficiently adapting according to the environment and able to maintain the chosen frequency response in the look direction always while minimizing the output power of the array. The capability of the smart antenna systems to track the user with the main lobe and interference with the nulls creates a significant impact on the current and future wireless sensor networks. In this work we have presented a routing scheme for sensor networks that utilizes smart antenna systems, where sensed data is sent to a receiving center using only local information and total absence of coordination between sensors, the data transmission in sensors are totally depends upon the beamwidth of smart antenna used. Due to the novelty of our proposal we pointed out the feasibility and necessity of using smart antennas in sensor networks, as well as the advantages that are presented to communication links due to their use. Our protocol is suited for those cases where unexpected changes to the environment (i.e. a fire, a person entering a restricted area, etc.) must be propagated quickly back to the base station without the use of complicated protocols that may deplete the network from its resources. Our protocol is very easy to implement as nodes do not have to decide whether or not to forward the message. The protocol ensures packet delivery and low energy consumption solely with the use of INLMS beamforming based smart antenna systems on sensor nodes. Network performance is measured in network throughput, lifetime, end to end delay and beam width of antenna used, it is clear from results that our INLMS based transmission scheme outperform the traditional LMS and NLMS based beamforming. We plan to continue this line of research by also considering “random” paths (not necessarily optimal) so that data is propagated to the destination. “Randomness” could be applied in the choice of the node beam direction, the transmission power, or the node antenna’s beam-width (i.e. with the use of variable gain switched beam antennas). Finally, mobility of sensors should be considered, so that networks using robotic sensors could be accounted for in the future. Of course, for this to be of any value, the protocol must again use only local information and no coordination between sensors.

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